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Control of the Tennessee Eastman process using input-output models

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This paper presents a case-study where model predictive control is applied to control a nonlinear, open-loop unstable process called the Tennessee Eastman Challenge Process. Both the base case and transitions between different operating points are considered. The control scheme is based on an input-output model identified from plant data. The Model Predictive Controller (MPC) controller acts as a supervisory controller that dictates the setpoints for a lower level PID loop structure. Simulations are presented to illustrate its effectiveness or disturbance rejection and setpoint tracking. © 1997 Elsevier Science Ltd

The Tennessee Eastman (TE) plant-wide industrial process control problem is a challenge problem for testing control strategies[1]. The process is highly nonlinear and is open-loop unstable. The large number of measured and manipulated variables offer a vast range of choice of possible control strategies. This paper outlines a control scheme for the TE process at various modes of operation. The first section introduces the TE challenge problem and presents the proposed control structure. This section also discusses some of the work that is present in the literature. Some of these control studies are based on nonlinear first principle models which are not readily available. Therefore we then take a different approach and identify a process model using input-output plant data. Next, this model is used in a supervisory MPC framework and closed-loop simulation results are presented. Finally, conclusions are drawn.

The Tennessee Eastman plant-wide control problem

The TE plant-wide control problem, developed by Downs and Vogel[1], has served as a useful vehicle for testing control strategies developed by different investigators. The authors have put forth plant-wide control, multivariable control, on-line optimization, predictive control and identification as potential applications. The process is described through fifty differential equations that are nonlinear and coupled. The plant produces two products (G and H) from four reactants (A, C, D and E). Two other by-products are present in the form of an inert (B) and a by-product (F). The simultaneous, exothermic gas-liquid reactions taking place are:

$$A(g) + C(g) + D(g) \rightarrow G(liq)$$

$$A(g) + C(g) + E(g) \rightarrow H(liq)$$

$$A(g) + E(g) \rightarrow F(liq)$$

$$3D(g) \rightarrow 2F(liq)$$

The process has five major unit operations: reactor, product condenser, vapor/liquid separator, recycle compressor and product stripper. A schematic diagram of the process is given in *Figure 1*. The feed to the process is gaseous. The catalyst used is a non-volatile catalyst dissolved in the liquid phase. The gaseous products from the reactor pass through a condenser and subsequently the vapor/liquid separator where the condensed products are separated from the unconverted reactants. This stream of unconverted reactants then passes through the recycle compressor before re-entering the reactor. The desired products (G and H) are obtained from the base of the stripper column while the inert (B) and the by-product (F) are purged as vapors from the top of the vapor-liquid separator.

The base case mode of operation for this process specifies a production mass ratio of 50/50 for G/H at a rate of 7038 $kg\,h^{-1}$ each. Most of the existing studies focus on this base case only. The control objectives are typical of many industrial processes and are listed below:

1. Maintain process variables at desired values.
2. Keep process operating conditions within equipment constraints.

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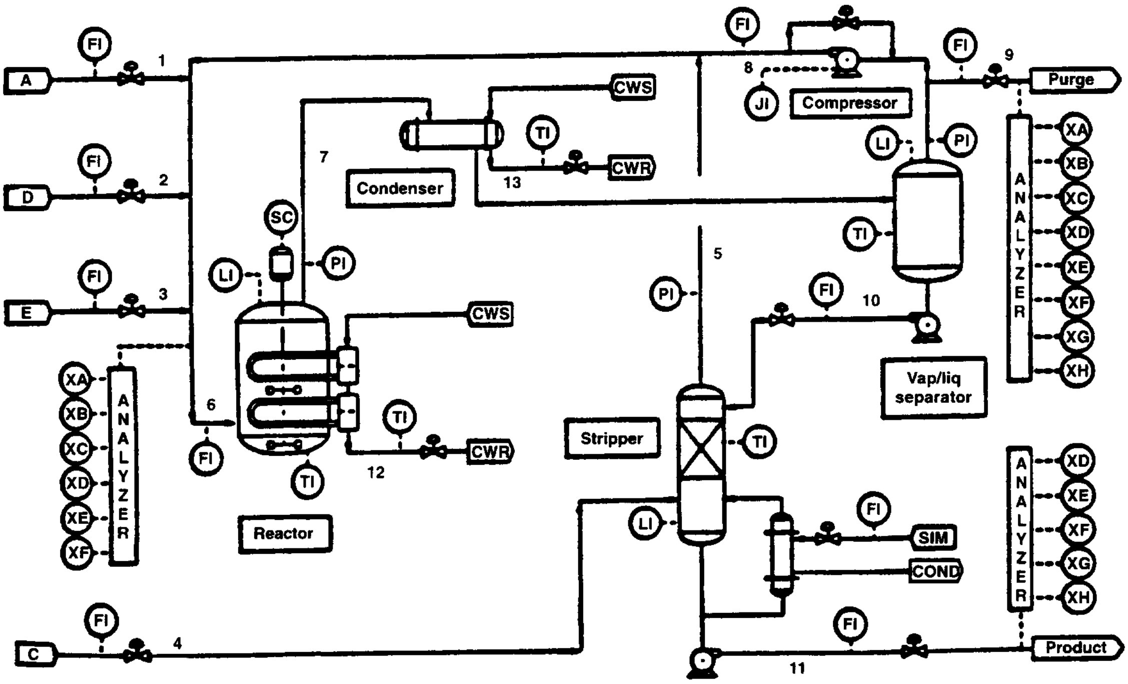

Figure 1 TE process flowsheet

3. Minimize the variability in the product rate and quality during disturbances. Product flowrate changes of more that ± 5% are especially to be avoided with significant frequency content in the range $8\,h^{-1}$ and $16\,h^{-1}$.
4. Recover quickly and smoothly from disturbances, product mix changes and production rate changes.
5. Minimize feed variability for the reactants that do not have significant hold-up.

The second control objective is enforced via hard constraints on some of the plant measurements, as summarized in *Table 1*.

Any viable control scheme must be designed to respect these constraints at all times. From the operational and control point of view, the variability of the product stream is very important as these variations affect the distillation unit downstream of the reactor that refines the products.

To achieve the control objectives presented above, there are 41 measurements and 12 manipulated variables available. Of these measurements, those pertaining to the product compositions are sampled measurements with significant dead-times.

Table 1 Operating and shut-down limits

Process variable	Normal operation limits		Shut-down limits	
	Low limit	High limit	Low limit	High limit
Reactor pressure	none	2895 kPa	none	3000 kPa
Reactor level	50 ($11.8\,m^3$) %	100 ($21.3\,m^3$) %	$2.0\,m^3$	$24.0\,m^3$
Reactor temp.	none	150°C	none	175°C
Prod. sep. level	30% ($3.3\,m^3$)	100% ($9.0\,m^3$)	$1.0\,m^3$	$12.0\,m^3$
Prod. sep. level	30% ($3.5\,m^3$)	100% ($6.6\,m^3$)	$1.0\,m^3$	$8.0\,m^3$

Downs and Vogel[1] provide a list of step changes and disturbances that have to be successfully accounted for by any control strategy. These will be discussed in later sections.

Supervisory MPC scheme

Successful control of the TE process requires stabilization of the reactor and satisfaction of the product specifications. Many researchers have developed alternative control strategies to meet these objectives. These include synthesis of control configurations using multiple SISO loops[2–4], Dynamic Matrix Control (DMC)[5] and nonlinear model predictive control[6,7]. Initially, the current work may seem similar to the DMC control strategy suggested by Palavajjhala *et al.*[5]. However, as mentioned in a later work[8], the DMC approach was tested only for base case setpoint changes, not against disturbances around the base case and setpoint changes to different modes of operation. Ricker and Lee address this issue more rigorously with the help of a lower order first principle model and on-line state estimation[6,7]. Using a multivariable controller with eight controlled and manipulated variables, Ricker and Lee were able to control the TE process in all modes of operation as suggested in the problem statement[7].

The present work is different from those in the literature in two main aspects. First, MPC is based on models identified from input-output data. Second, MPC is used in a supervisory mode to adjust the setpoints of PID controllers. It is shown that such a cascade configuration can effectively control the nonlinear plant using linear input-output models.

Banerjee and Arkun decomposed the design problem into two tiers[2]. The first tier controls the critical variables that affect the reactor stability; the second tier deals with variables which primarily affect the compositions of streams entering and leaving the reactor. Process variables in Tier I exhibit faster dynamics than those in Tier II. The recommended PID loops for both tiers are summarized in *Table 2*. This PID structure is adopted in this paper. The MPC controller is then used in a 'supervisory' role to manipulate the setpoints to these lower level PIDs to achieve different mode changes around the base case. As the underlying PID structure is stabilizing, this ensures that the process will remain stable when MPC is turned off.

Of the four loops in Tier I two (stripper level and separator level) are almost pure integrators and it has been shown that proportional controllers are sufficient for closed-loop stability and satisfactory performance[2]. Thus it was decided that MPC would not manipulate these loops. The other two variables (reactor pressure and reactor level) are included in a model predictive control scheme and their corresponding setpoints are chosen as the manipulated variables. The pressure and level play a significant role in the nonlinearity and stability of the reactor and so these variables were made available to the MPC controller.

For Tier II control, the two variables that are of primary concern are the product flow rate and the mass ratio of G and H in the product. To keep the number of manipulated variables small, it is decided to manipulate the feed streams of D and E to bring about changes in the product. The reason behind this choice is as follows. There is hardly any hold-up for the feed stream with A and C in it (stream 4). Therefore, it is not advisable to use the flowrate of this stream as a manipulated variable. Consequently, feed stream A cannot be the other input as this would upset the A/C ratio at the reactor inlet and upset the reaction stoichiometry. This leaves only D and E as the possible feed streams that could be used as inputs. *Figure 2* gives an overview of the control scheme in which MPC plays a supervisory role. The final choice of manipulated and controlled variables for the MPC scheme are given in *Table 3*.

Table 2 The lower level PID structure[2]

Tier	Loop	Controlled variables	Manipulated variables
	1	Reactor level	Compressor recycle value
	2	Separator level	Separator liquid flow
I	3	Stripper level	Stripper liquid flow
	4	Reactor pressure	Reactor cooling water flow
	1	Mole fr. G in prod.	D feed flow setpoint
	2	Mole fr. H in prod.	E feed flow setpoint
II	3	Mole fr. C in reactor feed	A and C feed flow setpoint (stream 4)
	4	Mole fr. A in reactor feed	A feed flow setpoint (stream 1)
	5	Mole fr. F in purge	Purge value

The issue of the process model to be used in the MPC scheme is addressed next.

Model identification

Most of the literature in the TE process control field revolves around using PID schemes to control the simulation model provided by Downs and Vogel[1]. An exception to this is a lower order first principles model developed by Ricker and Lee[7]. So far, however, the area of input-output modeling of the TE process for control purposes has been largely unexplored. In this section, input-output data will be used to identify an empirical model to be used by the MPC.

The first step in input-output modeling is generating the identification data. The TE plant, with its lower level PID loops, was excited with input sequences (for all the four manipulated variables) picked from uniform distribution, and the sampled outputs (for all four controlled variables) collected. These are shown in *Figures 3* and *4*, respectively. It should be noted that the generated data cover the expected range of operation and are therefore realistic.

Nonlinearity test

The plant data obtained for identification purposes is first subjected to a nonlinearity test statistic proposed by

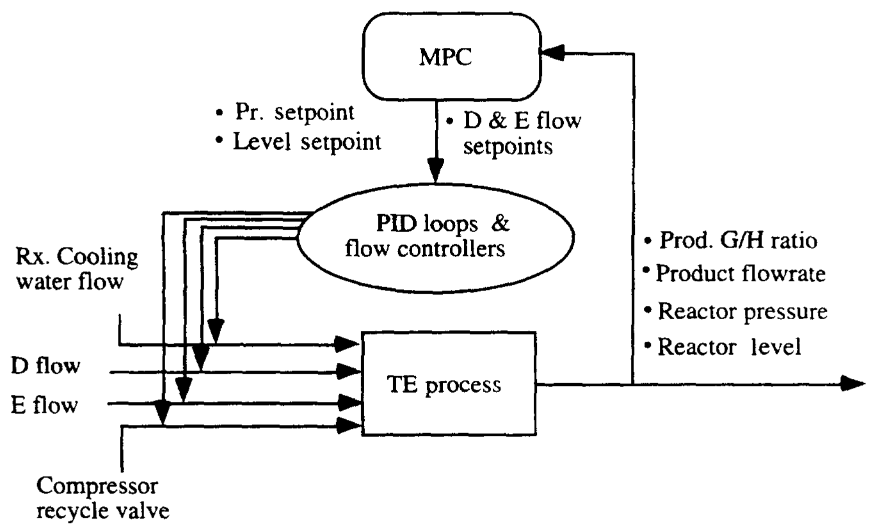

Figure 2 Supervisory MPC scheme

Billings and Voon[9] to check if a linear model is likely to explain the data. According to this test, the system generating the data is linear if and only if:

$$\phi_{zz^2}(\tau) = E[(z(k-\tau) - \bar{z})(z(k) - \bar{z})^2] = 0 \text{ for all } \tau \quad (1)$$

where $z(k)$ is the measured output value at time k and $\bar{z}$ is the sample mean. This can be approximated by:

Table 3 Manipulated and controlled variables in MPC

Controlled variable	Manipulated variable
y_1: Reactor pressure	u_1: Reactor pressure setpoint
y_2: Reactor level	u_2: Reactor level setpoint
y_3: Product flow rate	u_3: D feed flow setpoint
y_4: Mass ratio of G/H in product	u_4: E feed flow setpoint

$$\phi_{zz^2}(\tau) \approx \frac{1}{N}\sum_{k=\tau}^{N}(z(k-\tau) - \bar{z})(z(k) - \bar{z})^2 \quad (2)$$

If the system generating the data is linear then the quantity given in Equation (2) has a Gaussian distribution. Therefore, a test statistic can be developed for large sample sizes and it can be said with a confidence level of 95% that the process generating the data is linear if:

$$\left| \frac{\phi_{zz^2}(\tau)}{\sqrt{\phi_{zz}(0)}\sqrt{\phi_{z^2z^2}(0)}} \right| \leq \frac{1.96}{\sqrt{N-\tau}} \quad (3)$$

The results of this test are shown in *Figure 5*. It can be seen that the test statistic lies within the 95% confidence

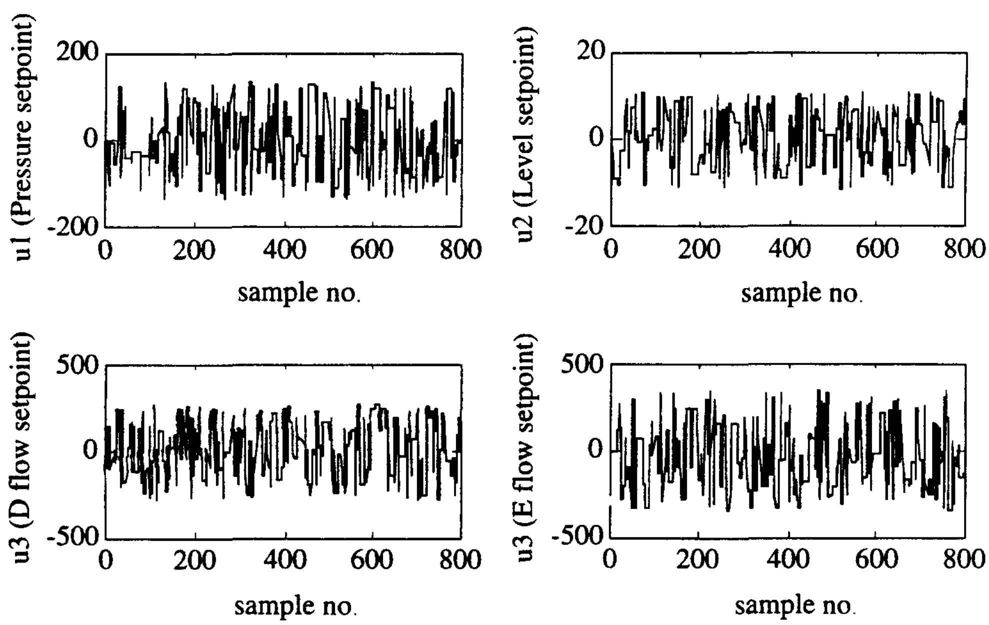

Figure 3 Input data used in identification of model

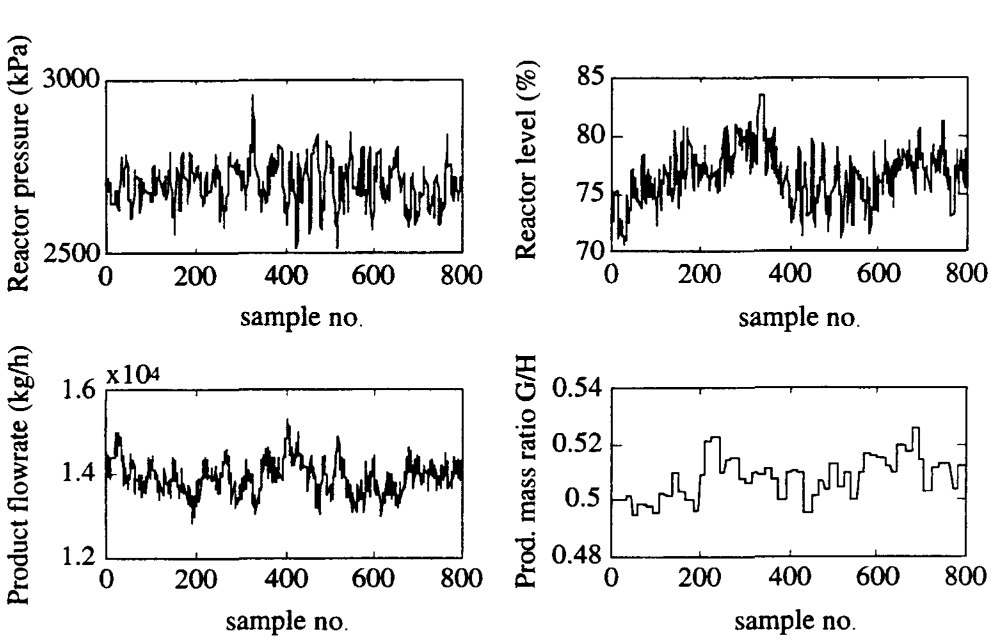

Figure 4 Output data used in identification of model

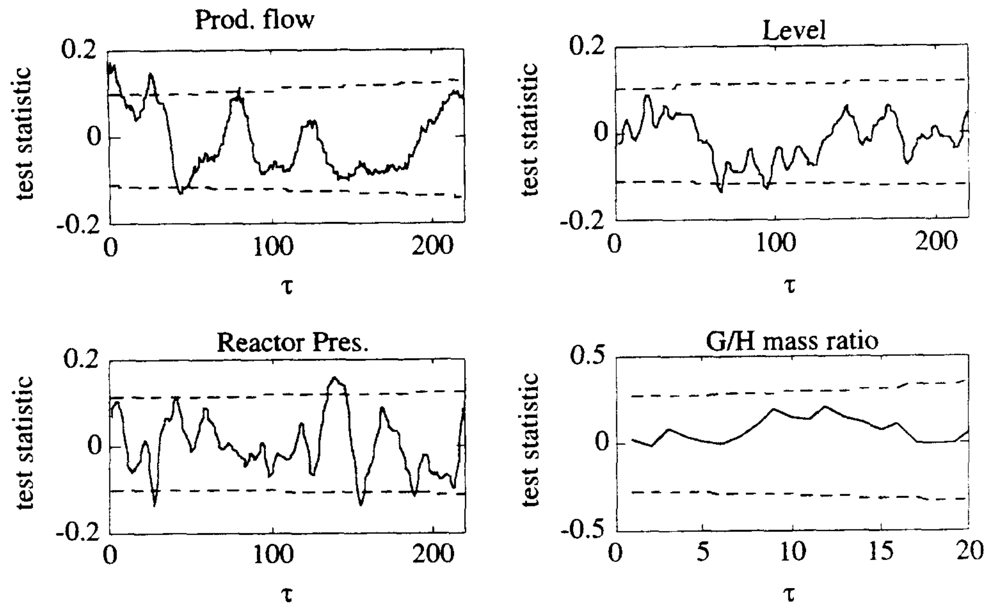

Figure 5 Nonlinearity test results

bounds for all the outputs for most of the time. In fact, for the G/H mass ratio it is within bonds *all* the time. When a series of individual step tests were conducted on the TE process with varying magnitudes of the inputs in both positive and negative directions, the results are almost symmetric and did not suggest any significant nonlinearities and directionality problems. However, one should be cautious with this conclusion. As stated in the introductory passage, the open-loop process is in fact nonlinear. Yet closing certain PID loops, as was done during generation of the identification data results in a process which behaves in a linear manner. With PIDs masking the nonlinearities. one can then proceed with the development of a linear model, *at least as a first attempt*.

A standard linear identification package (MATLAB System Identification Toolbox) was used to identify the four input/output models for the four controlled variables. The first two outputs (reactor level and reactor pressure) are modeled as single-input-single-output (SISO) systems. For these two models, the outputs are reactor level and pressure, and the inputs are their respective setpoints. The remaining two outputs (product flowrate and product mass ratio of G/H) are modeled as multi-input-single-output (MISO) systems. The logic behind this choice of structures is as follows. Reactor pressure and reactor level can be controlled by simply manipulating their respective setpoints and employing lower level PI controllers to achieve them without using D or E flowrates. Therefore, this structure simplifies the controller's task as it can now focus on using D and E flowrates solely for product composition and flow control. The resulting models are shown in *Table 5* and their respective single step predictions are shown in *Figure 6*. At this point, an important fact has to be pointed out. The sampling time used

Table 4 Tuning parameters for MPC for plant-wide control of the TE process

	Tuning parameters				Constraints	
	P	M	γ	λ	Min	Max
Output 1	20	—	0.005	—	0.0	3000.0
Output 2	20	—	0	—	500	100.0
Output 3	20	—	5.0	—	$-\infty$	∞
Output 4	20	—	5.0	—	$-\infty$	∞
Δu_1	—	2	—	500	$-\infty$	∞
u_1	—	2	—	—	-100.0	150.0
Δu_2	—	2	—	20.0	$-\infty$	∞
u_2	—	2	—	—	-15.0	15.0
Δu_3	—	2	—	15.0	$-\infty$	∞
u_3	—	2	—	—	-2900.0	2200.0
Δu_4	—	2	—	15.0	$-\infty$	∞
u_4	—	2	—	—	-3800.0	3800.0

Table 5 The regressors and parameters of the input output model, model type: $y(k) = \sum_{i=1}^{N} a_i y(k-i) + \sum_{j=1}^{M} b_j u(k-j)$

Regressors	θ			
	Output 1	Output 2	Output 3	Output 4
y(k−1)	1.157	0.95	0.528	0.235
y(k−2)	−0.338	−0.256	0.357	0.128
u_1(k−1)	0.0669	—	0.0325	0.158
u_1(k−2)	0.0457	—	−0.045	0.213
u_1(k−3)	0.06396	—	−0.11	−0.0134
u_1(k−4)	—	—	—	−0.134
u_1(k−5)	—	—	—	0.081
u_2(k−1)	—	0.0598	−0.0048	−0.0097
u_2(k−2)	—	0.034	0.0118	0.0136
u_2(k−3)	—	0.0452	−0.0069	−0.0088
u_2(k−4)	—	—	—	0.012
u_2(k−5)	—	—	—	−0.0508
u_3(k−1)	—	—	0.0157	−0.029
u_3(k−2)	—	—	0.0082	−0.0094
u_3(k−3)	—	—	−0.0122	0.069
u_3(k−4)	—	—	—	0.0346
u_3(k−5)	—	—	—	−0.0539
u_4(k−1)	—	—	0.0262	0.0359
u_4(k−2)	—	—	−0.0017	−0.00006
u_4(k−3)	—	—	−0.0018	0.0539
u_4(k−4)	—	—	—	−0.0588
u_4(k−5)	—	—	—	−0.0704

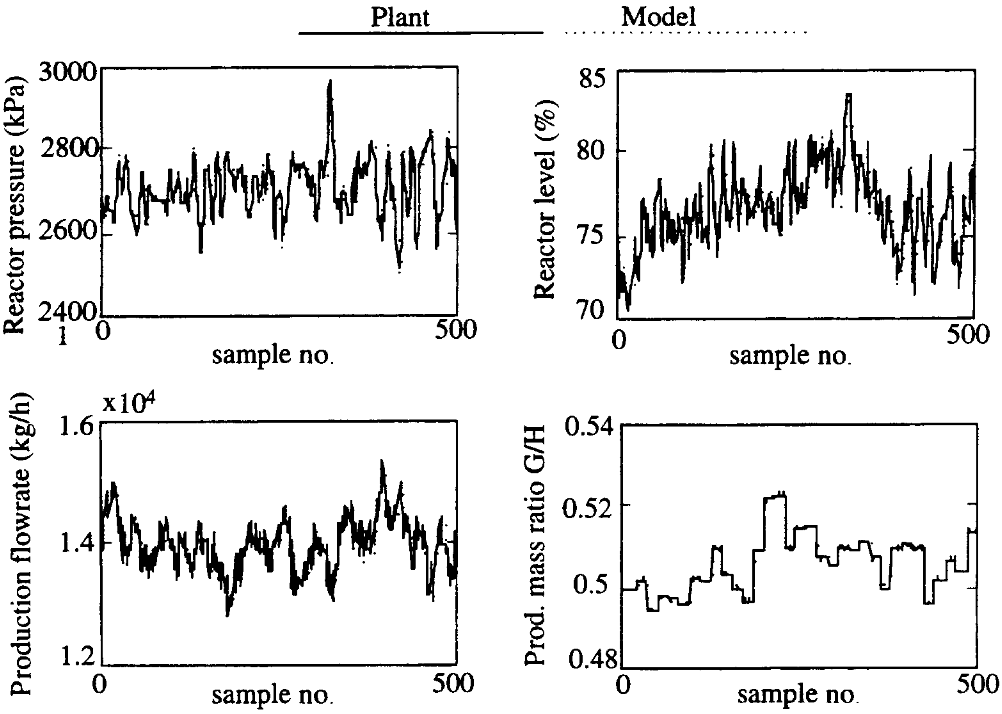

Figure 6 Single-step predictions of the input-output model

in the identification data was 1 min. However, the last output, the product composition, has a dead-time of 15 min and a sampling time of 15 min. Therefore, we first identified a model with a 15 min sampling time. Next, this model was used to predict the plant output. Then, these data were interpolated linearly to give data points at 1 min intervals. The resulting data were used (along with the input sequence) to identify the linear model given in *Table 5*. This approximation aids the MPC calculations in effective control of the process, as will be shown in the results section.

Controller algorithm

The MPC algorithm is the well-known and widely implemented Quadratic Dynamic Matrix Control (QDMC) algorithm. At any sampling time, the model prediction into the future is comprised of three parts:

$$\hat{Y} = \hat{Y}^{past} + S\Delta u + D \tag{4}$$

where $\hat{Y}^{past}$ is the effect of past inputs on the future outputs. This prediction is obtained from the process model which is the linear model identified above. S is the matrix of step response coefficients; Δu is the vector of future input moves and D is the estimate of the plant-model mismatch. The step-response model was obtained by conducting a series of step tests. Positive and negative step changes were introduced in the manipulated variables given in *Table 3* and the output results were averaged. Control moves were then computed from a standard constrained quadratic optimization.

Simulation results

This section presents simulations where the input-output model identified in the previous section is used by the supervisory MPC scheme. In their paper, Downs and Vogel[1] recommend 4 setpoint changes and 20 load changes. However, they recommend 4 of these 20 disturbances for evaluating control strategies. In the following simulations, these 8 cases (4 setpoint and 4 load changes) are presented. In all the simulations, the sampling time is equal to 1 min and the values for the prediction and move horizons are 20 and 2, respectively (see *Table 4*). In all the simulations in the subsequent sections, the tuning parameters for the lower level PID controllers are kept the same. MPC tuning parameters (weights on the inputs and outputs, γ and λ; prediction and move horizon, **P** and **M**) are largely the same for all setpoint and disturbance rejection simulations. In a few cases, the input and output weights are adjusted due to the performance requirements. These instances are noted in the text.

Setpoint changes

The first simulation presents a -15% step in the product flowrate from $14208\,\mathrm{kg\,h^{-1}}$ to $12095\,\mathrm{kg\,h^{-1}}$. *Figure 7* shows how MPC adjusts the manipulated variables to bring about the change. It is seen that the product flowrate and G/H mass ratio remain within the stipulated $\pm$ 5% limits from their respective setpoints. These limits are shown as horizontal dashed lines in the plots. Due to the relatively large input weights chosen (see *Table 4*), reactor level setpoint is kept constant and pressure setpoint is adjusted very little by MPC. Also, with small output weights chosen, pressure and level are

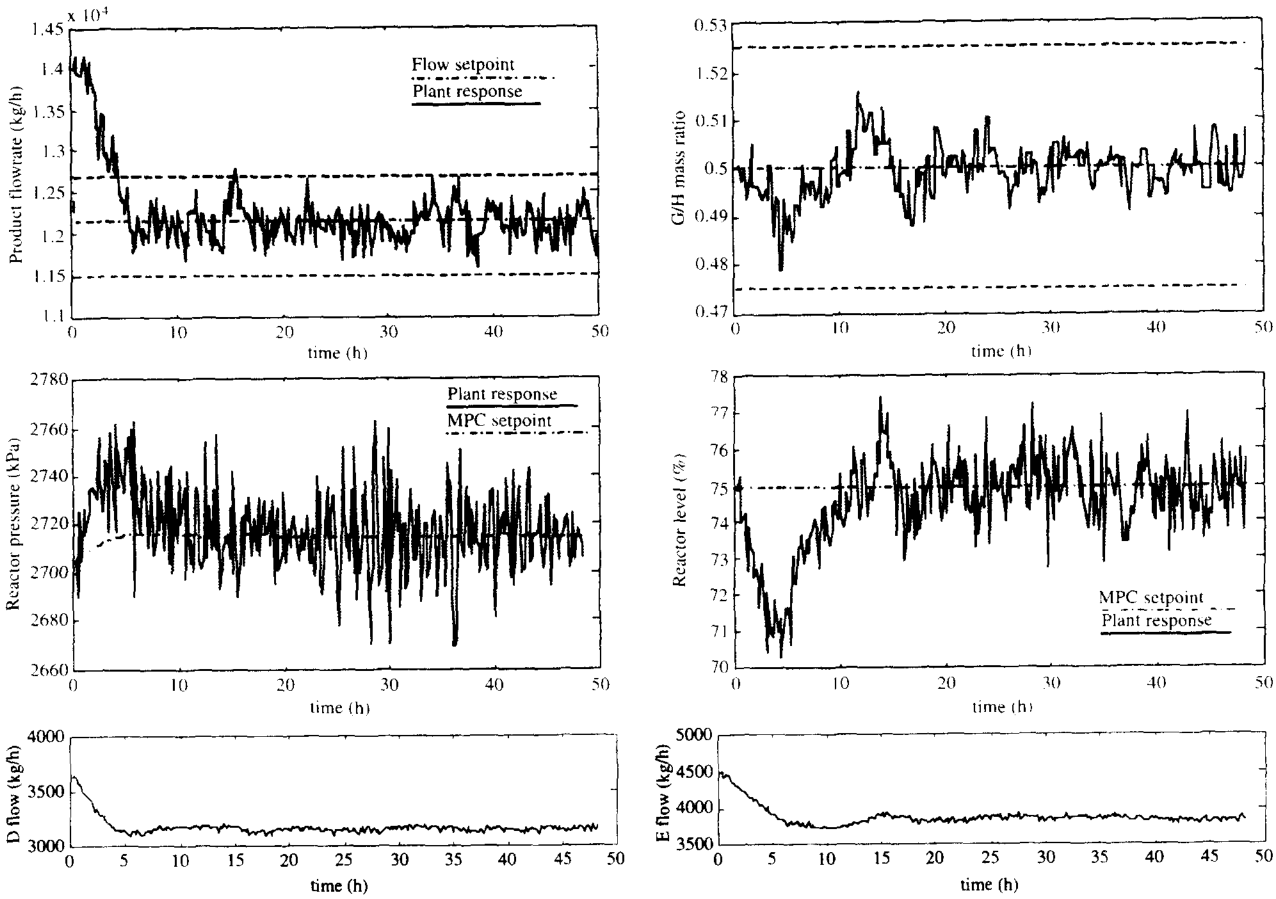

Figure 7 A step of –15% in production flowrate

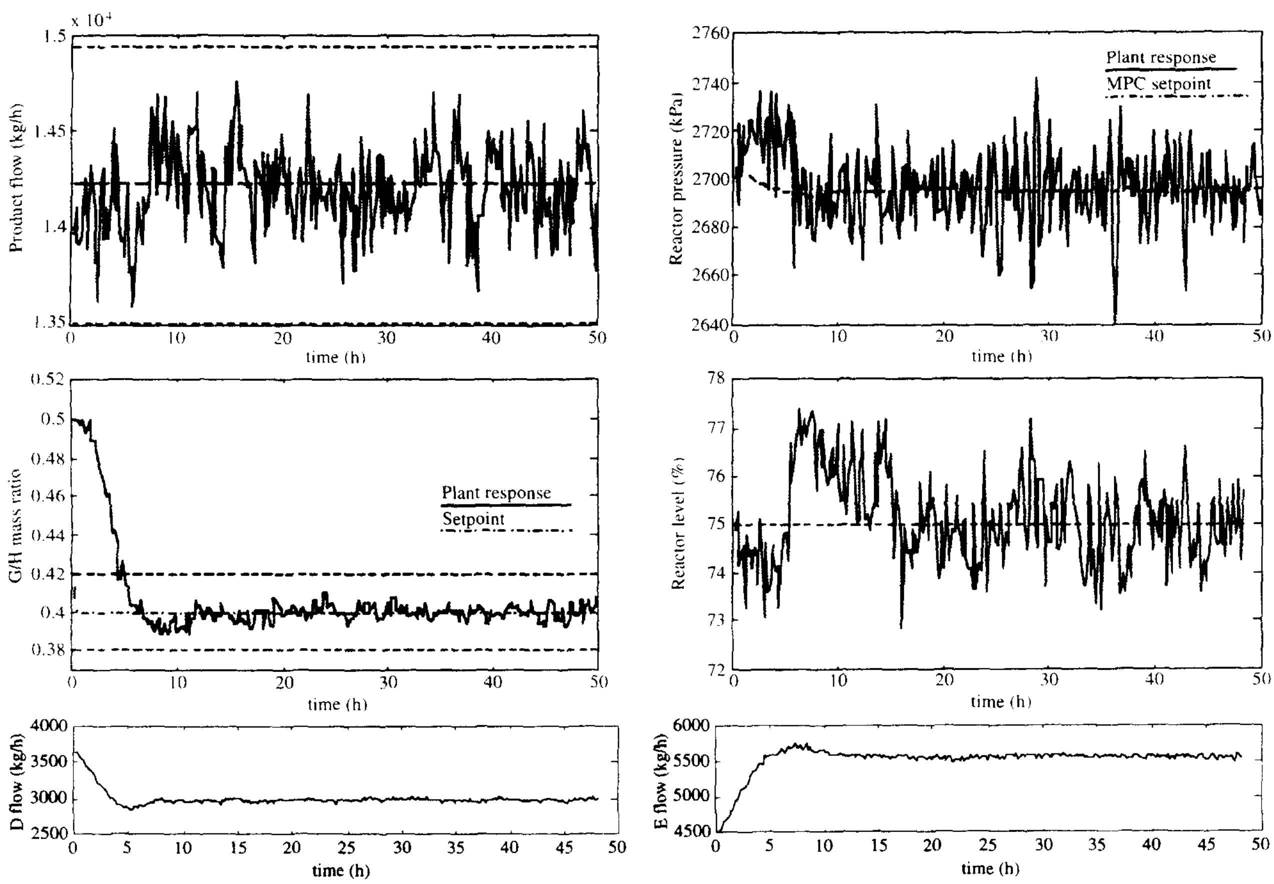

Figure 8 Step in G/H mass ratio in product from 50/50 to 40/60

not very tightly controlled but they remain within their shut-down limits. Performance is acceptable considering that the PID controllers were not retuned.

The second setpoint change administered is a step in the G/H mass ratio in the product from the base value of 50/50 to 40/60 G/H. It is seen from *Figure 8* that MPC is able to achieve this setpoint change as well.

The third setpoint change requires the reactor pressure to be lowered by 60 kPa. Given the present and final desired values of reactor pressure, MPC computes the optimal setpoint moves between the initial and final desired values. The PID pressure loop tracks this setpoint profile as shown in *Figure 9*. The output weight of reactor pressure is increased from the value of 0.005 (see *Table 4*) and set equal to 5.0 to achieve tighter control. The need to change the output weight for pressure in this simulation arises due to the choice of controlled and manipulated variables in the MPC framework. Downs and Vogel[1] do not specify any variability limits on the reactor pressure and level as long as they are within their shut-down limits. Therefore, it is advisable that MPC be aware of these limits in the form of output constraints. Thus it was decided that reactor pressure and level should be designated the status of output variables with relatively insignificant output weights. However, in special setpoint change scenarios such as this one, the pressure is the main controlled variable; therefore, the output weight had to be increased. It is seen that the desired setpoint is reached within 5 h from the onset of the simulation. The product flowrate and the mass ratio of G/H in the product remain within the limits. *Figure 10* shows the response of the lower level PI controllers in maintaining their respective setpoints.

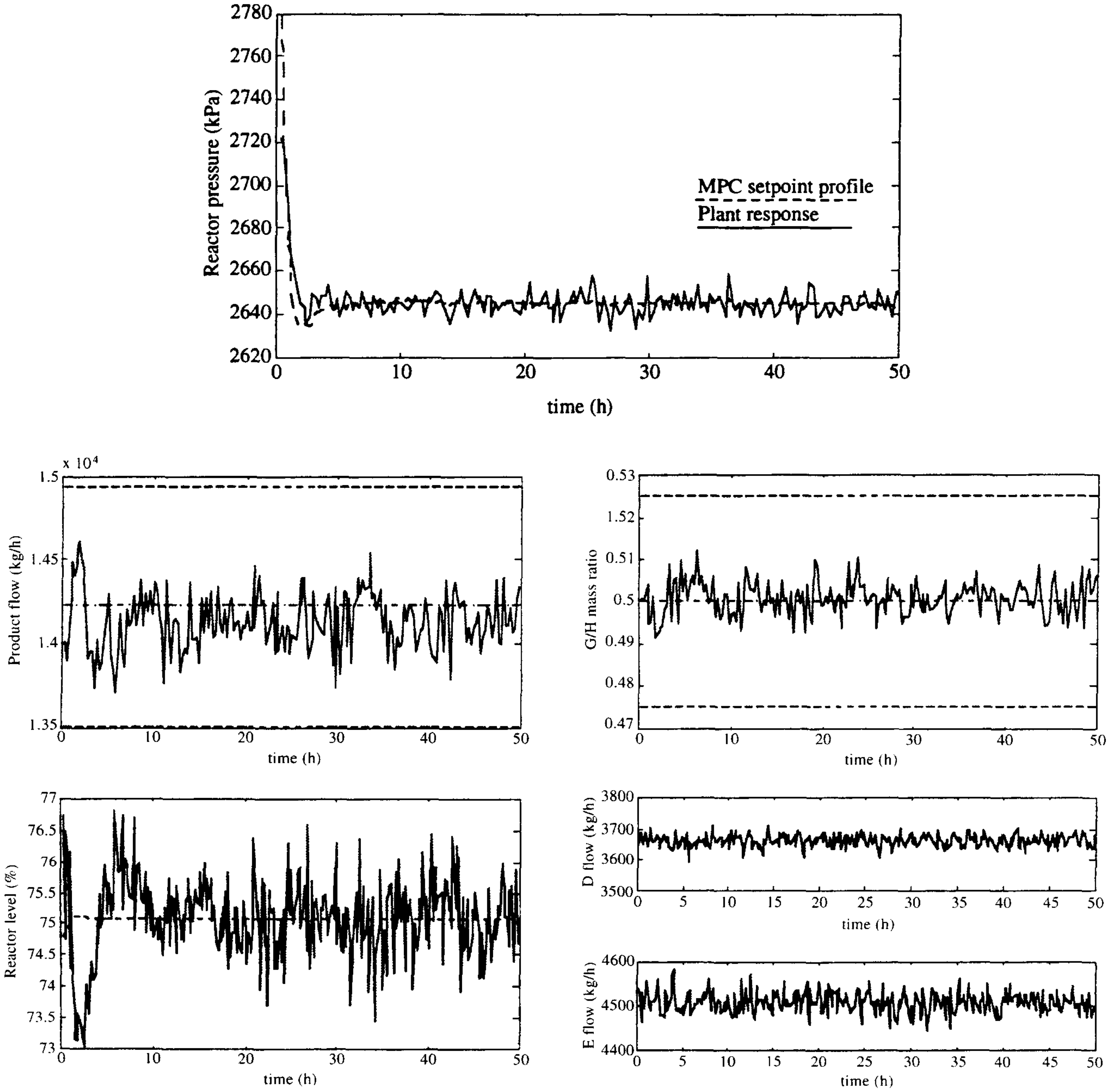

Figure 9 Step of –60 kPa in reactor pressure

The last recommended step change is a step in the composition of B (the inert) in the purge gas from 13.82 to 15.82%. Banerjee and Arkun[2] have shown that purge gas composition of B can be influenced by changing the reactor pressure. The physical reason for this is as follows: increasing the reactor pressure results in increase in the vapor/liquid separator pressure which increases the lower molecular weight components in the recycle and results in lowering of by-product F in the purge. This causes the purge valve to close and increase the mole % B in the purge and the recycle stream. In fact, to bring about the desired setpoint change in B, the reactor pressure has to be increased from the base value of 2705 to about 2805 kPa. This simulation is therefore identical to the previous setpoint change except that the desired change in reactor pressure is different. It is seen in *Figure 11* that MPC easily achieves the desired change in composition of B in the purge.

Disturbance changes

The first disturbance is a step disturbance that affects the A/C ratio in feed stream 4. As both A and C figure prominently in the rate equations, this disturbance affects the product flowrate and composition. In this case, the MPC controller manipulates the inputs to keep the controlled variables within operational specifications (see *Figure 12*). The product flowrate and composition are both within the 5% variation limit throughout the duration of the simulation. The tuning parameters for this simulation are as given in *Table 4*.

The second disturbance is a step in the temperature of the reactor cooling water flowrate. This disturbance affects the reactor temperature and thus the reactor pressure. Tier I PI controller that governs the reactor pressure is capable of handling this disturbance on its own by manipulating the reactor cooling water flowrate. However, MPC manipulates the pressure setpoint and D and E flowrates in order to keep the product compositions from varying too much from their targets. This is shown in *Figure 13*.

The third disturbance comprises random variations in A, B and C compositions entering via stream 4 into the reactor. This causes the PIDs and MPC to change the flow setpoints for all the four feed streams which causes oscillations in the product properties. *Figure 14* shows that the 5% variability limit is indeed violated for a short time for the product flowrate during the simulation.

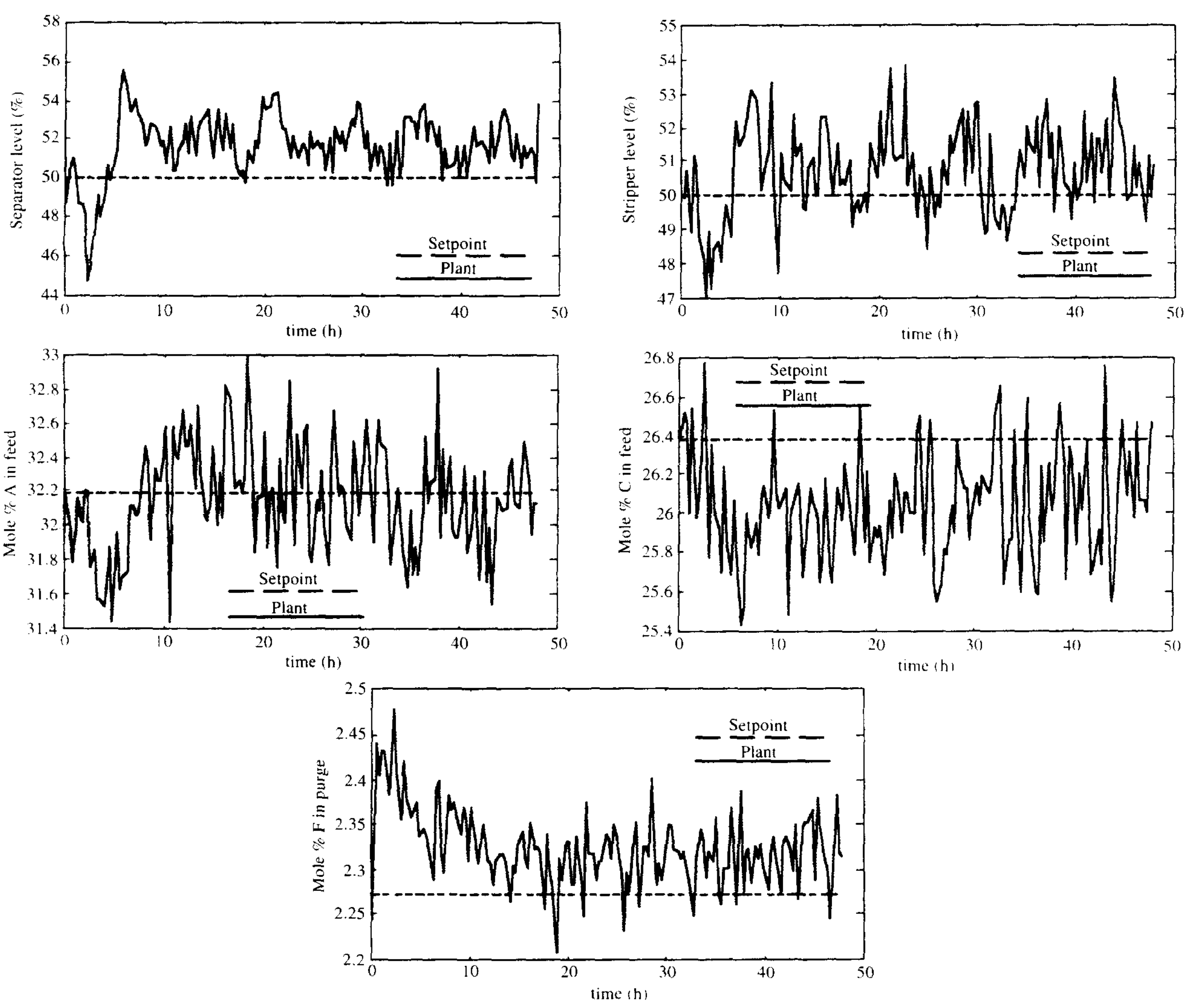

Figure 10 Lower level PI response for the simulation shown in *Figure 12*

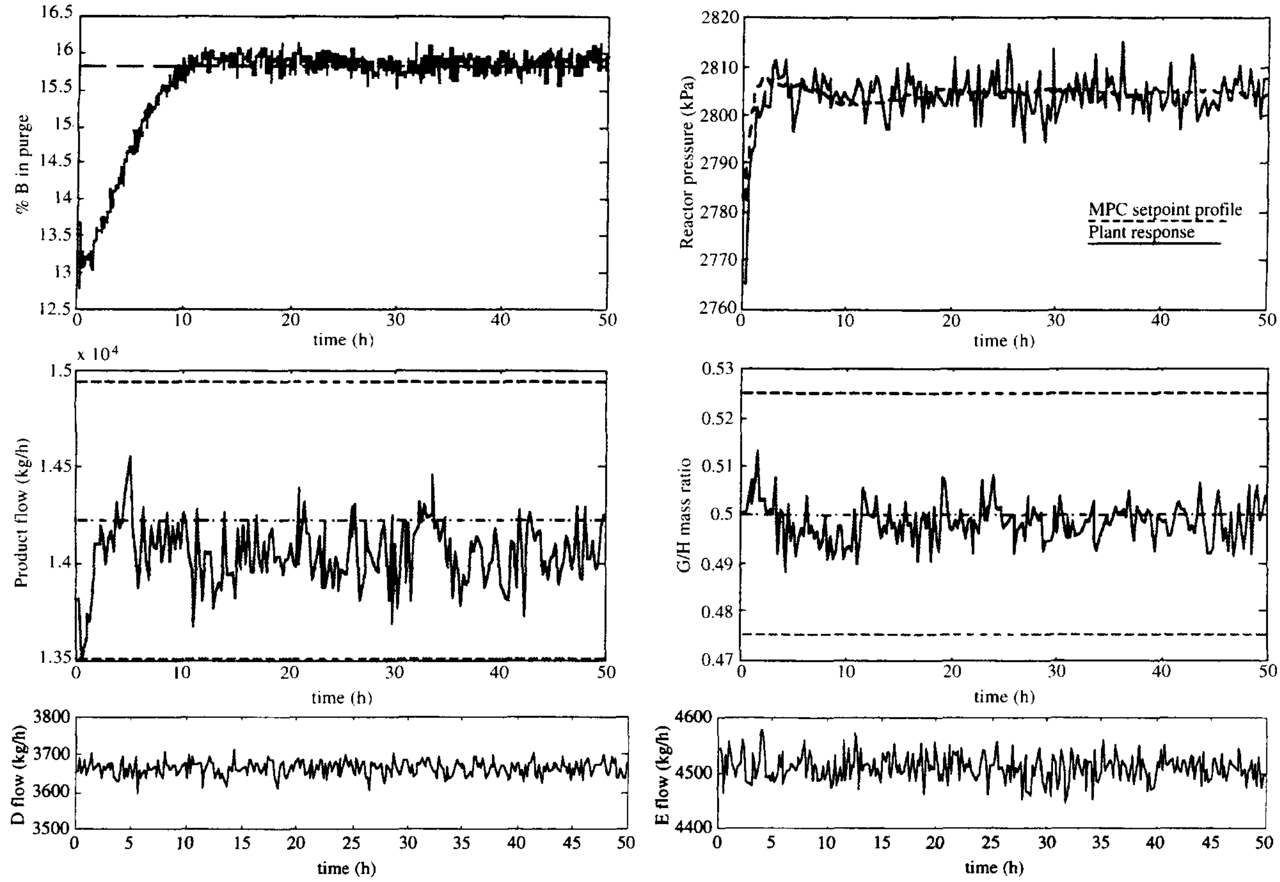

Figure 11 Step change in mole % of B in purge from 13.82 to 15.82%

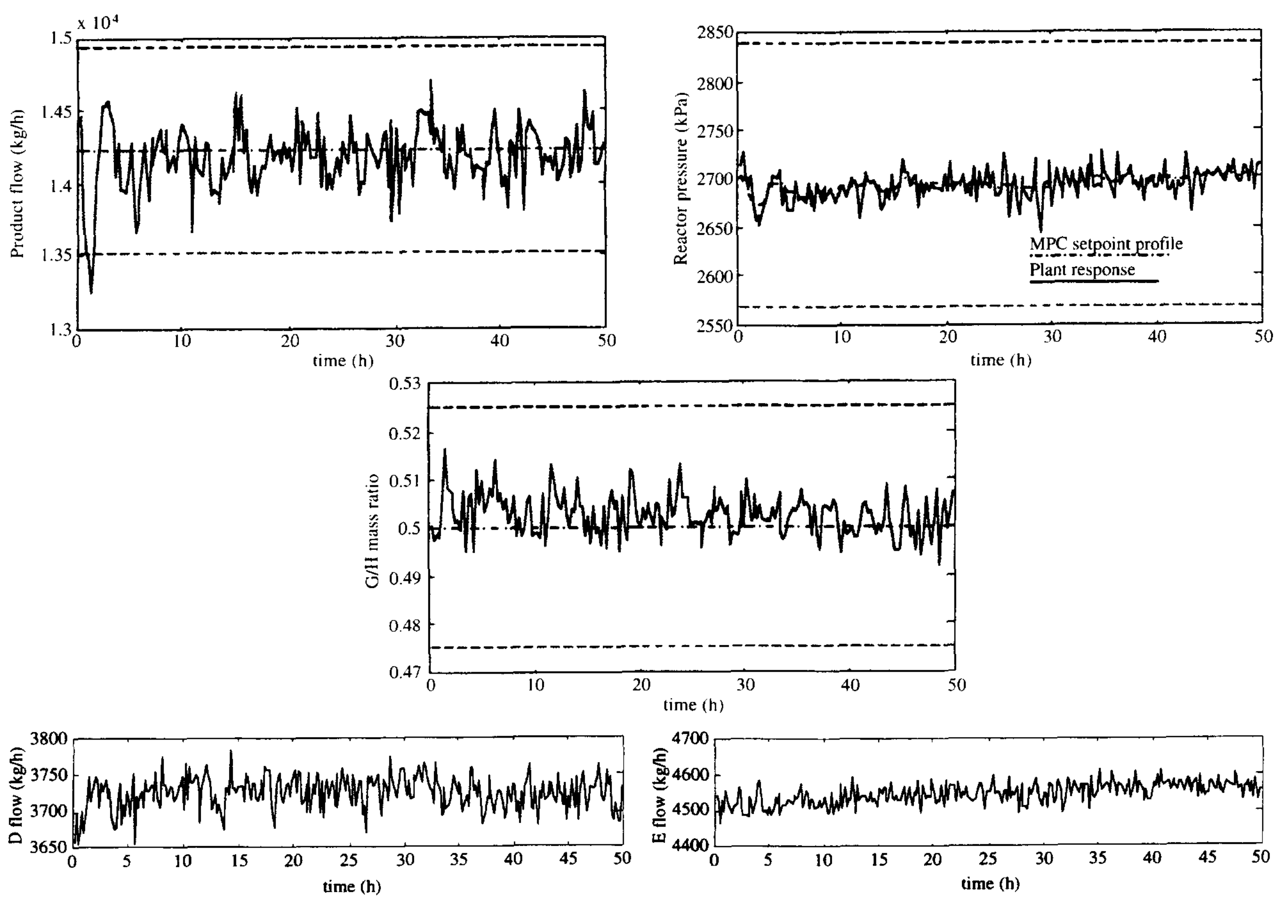

Figure 12 A step disturbance in A/C feed ratio

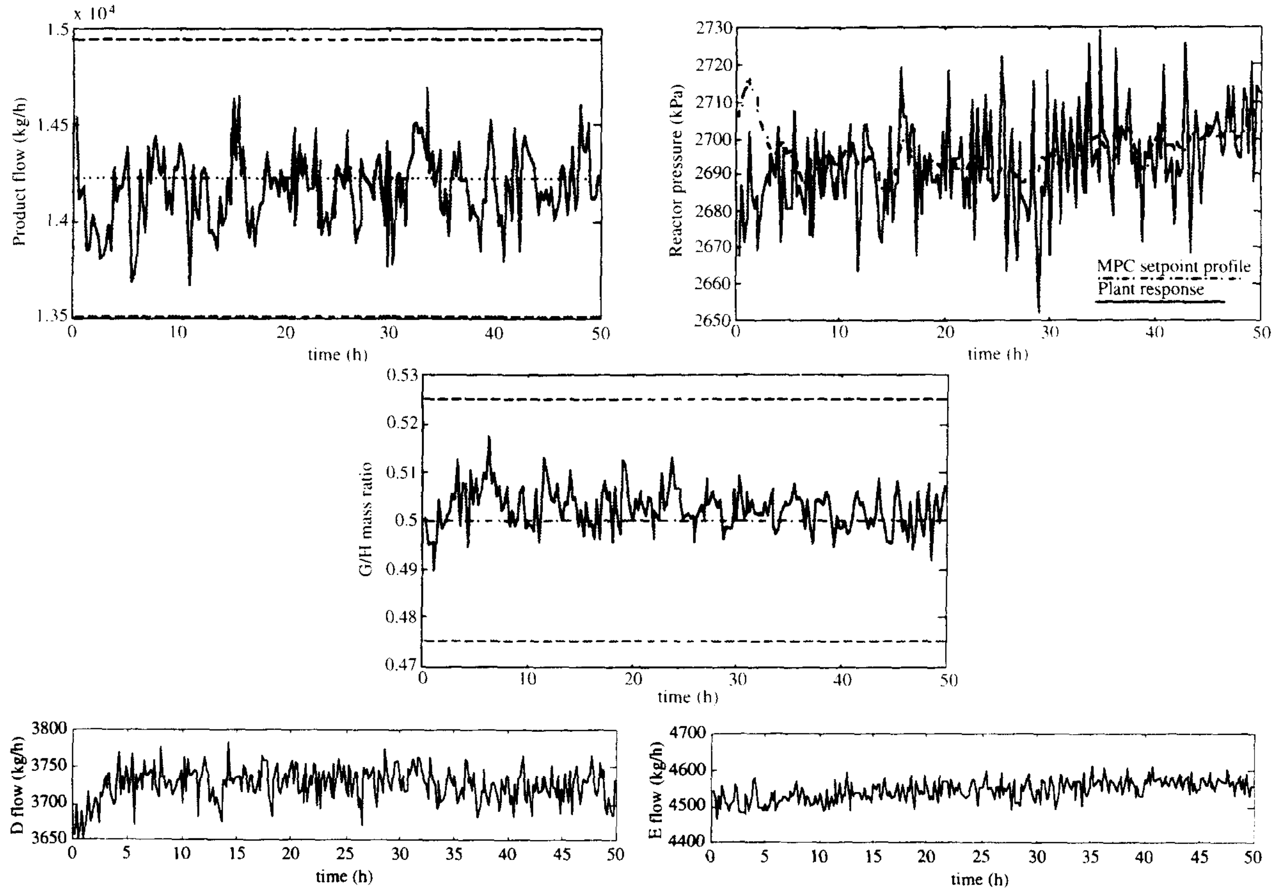

Figure 13 A step disturbance in reactor cooling water temperature

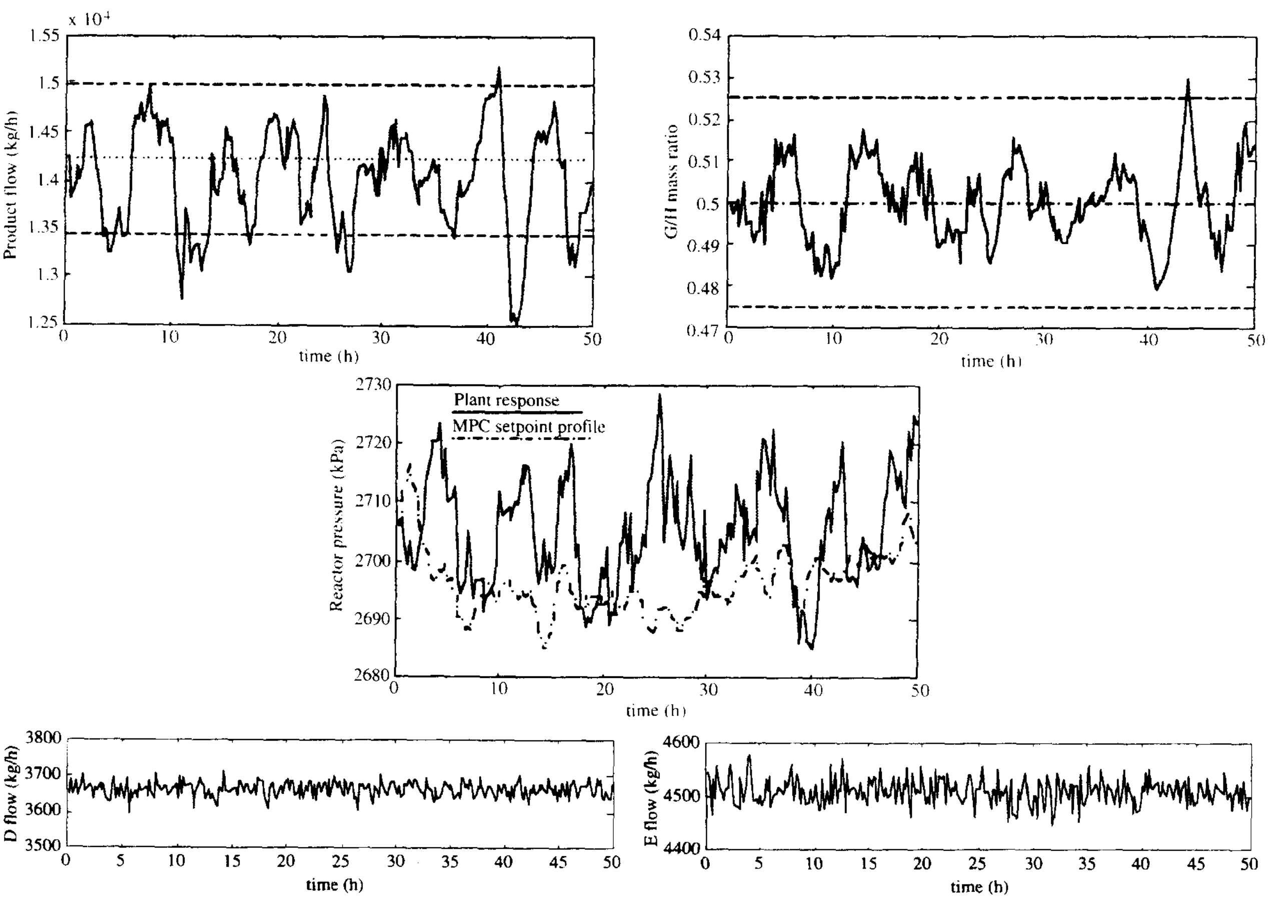

Figure 14 Random variations in feed stream C composition

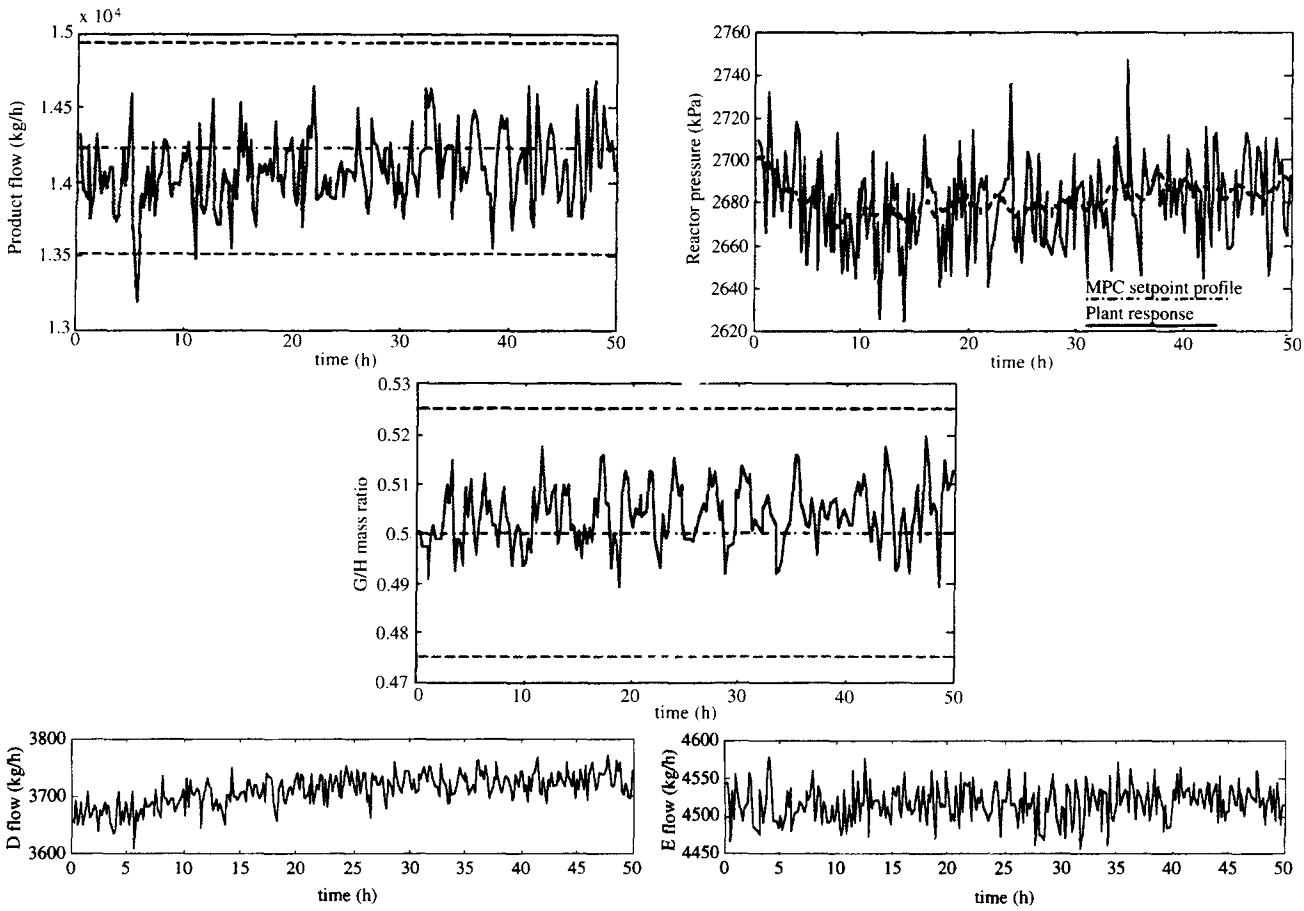

Figure 15 Effect of random variations condenser cooling water temperature along with sticking condenser cooling water valve

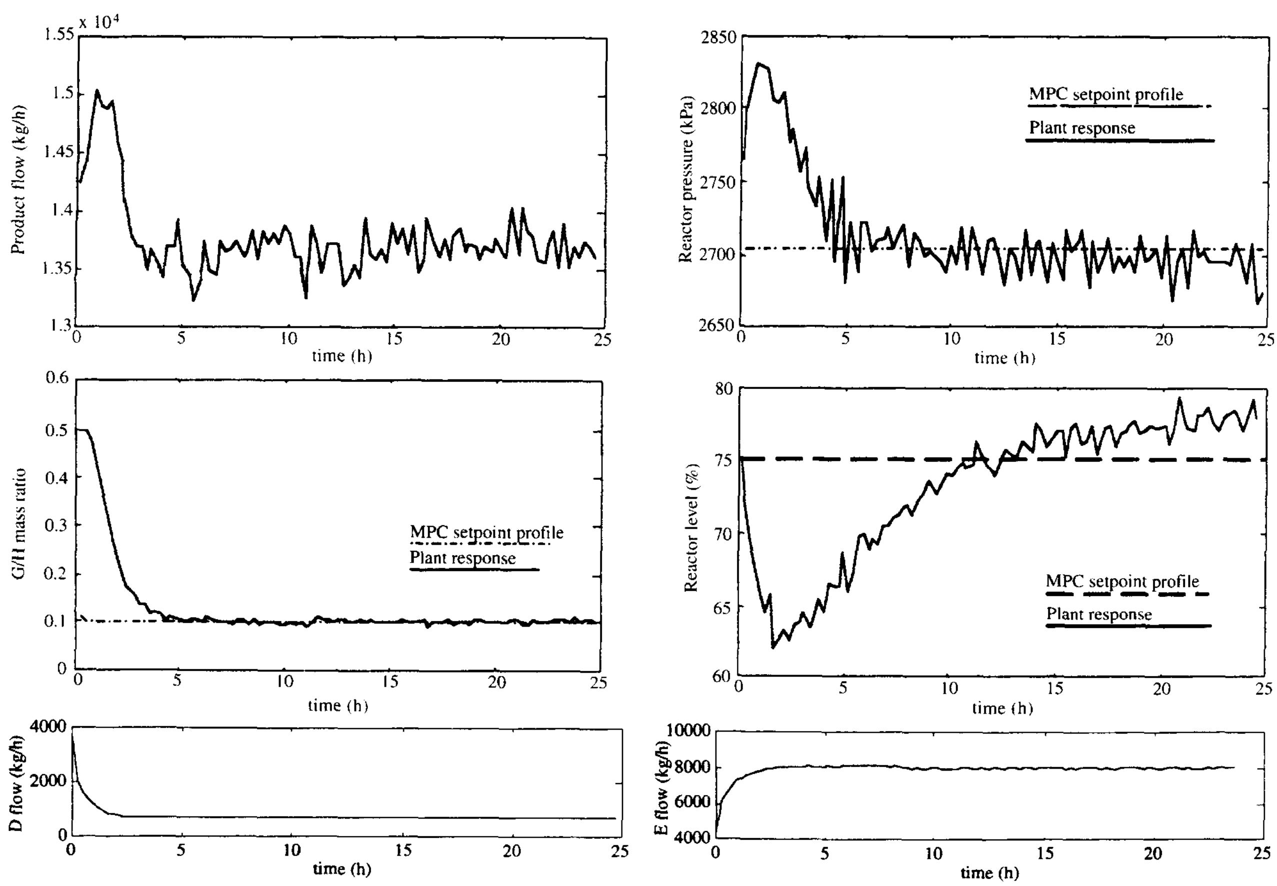

Figure 16 Step in G/H mass ratio in product from 50/50 to 10/90

However, the frequency content of these variations is below $8\,h^{-1}$ (which can be verified using spectral analysis); thus the control objectives are met.

The last load change is a random change in the condenser cooling water temperature. This disturbance directly affects the reactor pressure as the condenser temperature affects the liquid volume in the recycle. MPC adjusts the reactor pressure setpoint to account for the change in reactor pressure due to this disturbance and all product variables are controlled satisfactorily (*Figure 15*).

Transition to other modes of operation

The ability to take the TE plant smoothly from one mode of operation to another is a requirement for any successful control algorithm. This transition has to be smooth and quick to avoid producing large quantities of off-spec product. This requirement is quite practical in nature as more and more plants are being built and modified to produce multiple products. The ability to make more than one product gives a plant a competitive edge in today's industry.

Two simulations are presented next which demonstrate the transition from the base operating point 50/50 to 10/90 G/H ratio and 90/10 G/H mass ratio which are recommended by Downs and Vogel[1]. In the first simulation, the transition to the lower value of G/H is presented. *Figure 16* shows the results from this simulation. It is seen that the process takes about 10 h to settle down at the new operating region. The production flowrate drops from its original value to a new value which is within the desired specifications and on target as specified by Downs and Vogel[1] who, in the statement of the problem, further suggest that the transitions be carried out with minimal changes in the operating

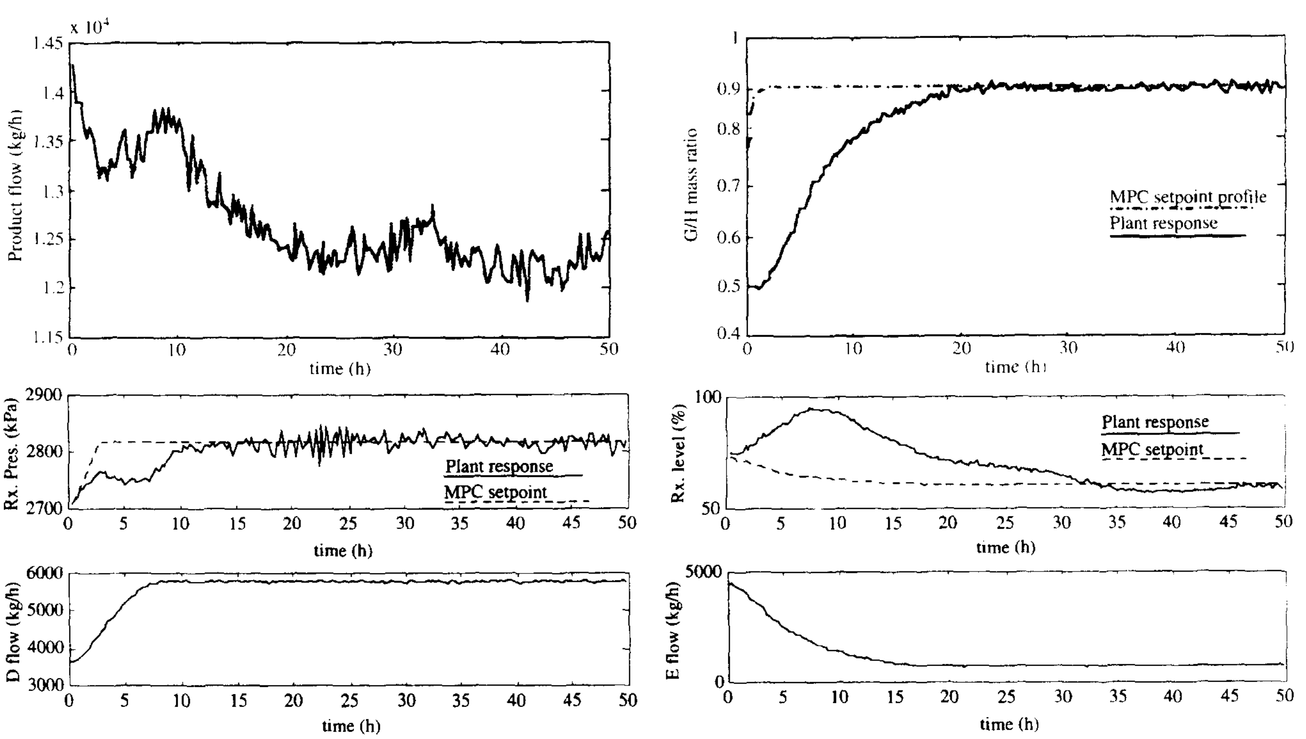

Figure 17 Step in G/H mass ratio in product from 50/50 to 90/10

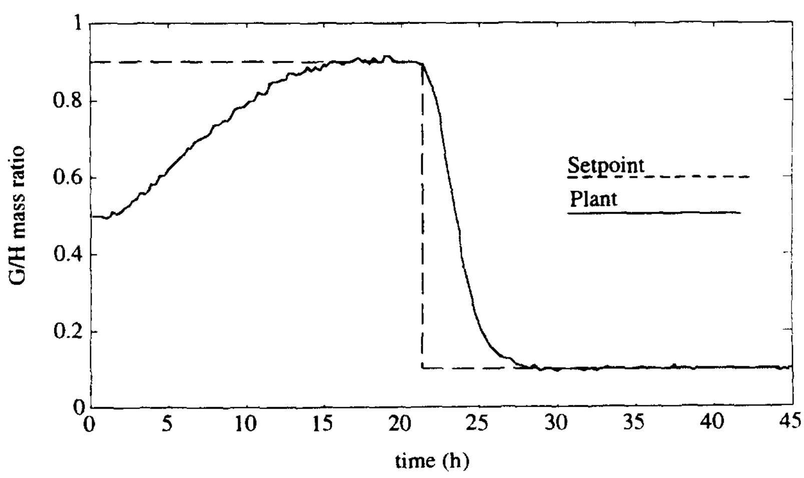

Figure 18 Continuous change in G/H mass ratio in product from 50/50 to 90/10 to 10/90

conditions. We have found that the first mode change 50/50 to 10/90 G/H could be carried out at the base case values of operating reactor pressure and level. Therefore, as seen in *Figure 16*, MPC was not allowed to change these setpoints.

Figure 17 shows the simulation where the setpoint for the product composition is raised from 50/50 to 90/10 G/H. It can be seen that MPC manipulates the given inputs adequately to bring about the desired changes. Unlike the first mode change, MPC has to change the reactor pressure and level to achieve this transition. Finally, *Figure 18* shows the output response when the process is taken through a continuous transition between the three modes of operation. Throughout the above transition simulations, the tuning parameters used are as shown in *Table 4*.

Conclusions

In this paper, a lower level PID structure has been used to stabilize the TE process and MPC is used in a supervisory role for product control. The results are quite promising for such a simple controller construction. This work is not as comprehensive as that of Ricker and Lee[7] where nonlinear modeling, on-line estimation and a larger scale of MPC controller was used which gave excellent results. However, the main point that has been put forward in this work is that, given a reliable lower level PI structure, it is possible to construct a simple MPC controller, with as few as two controlled outputs, that can be used to achieve the desired product transitions. MPC dictates setpoints to the lower level PIDs for the desired product response. With the lower level PIDs in place, the process is seen to display less directionality and nonlinearities and this allows the use of linear identification methods for identification of a model for the process. It is shown that the MPC controller, with this input-output model in its control scheme, displays acceptable closed-loop performance and is able to achieve the proposed control objectives.

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